Beyond the Third Pillar of Basel Two: Taking Bond Market Signals Seriously

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Abstract. *The logic behind the indirect channel of market discipline presumes that the pricing of bank debt in the secondary market, if accurate, conveys to supervisor and other market participants a reliable signal of bank's financial conditions and default risk. By collecting a unique dataset of spreads, ratings, and accounting measures of bank risk for a sample of large European banking organizations during the 1995–2002 period, we empirically test whether secondary market prices accurately reflect financial conditions of bank issuers. Our results complement the findings obtained by Sironi [Testing for market discipline in the European banking industry: Evidence from subordinated debt issues. Journal of Money, Credit, and Banking 35 (2003) 443-472] on the primary market of bank subordinated debt.*

Keywords: Banking regulation; Market discipline; Subordinated debt; Credit spreads
JEL classification: G21; G28

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1. Introduction

The particularly attractive idea to integrate market discipline into the prudential regulation of banks is not entirely new. Complying with a requirement of the American Congress, in April 1983 the FDIC[1] conducted a study aiming to assess the various reform options likely to strengthen market discipline in banking:

> "*We can promulgate countless new regulations governing every aspect of bank behavior and hire thousands of additional examiners to enforce them. This approach would undercut the benefits sought through deregulation, would favor the unregulated at the expense of the regulated, and would ultimately fail. The FDIC much prefers the other alternative: seeking ways to impose a greater degree of marketplace discipline on the system to replace outmoded government controls*". FDIC (1983, p.3)

From then on, market discipline and especially subordinated debt – as one of its privileged sources – have drawn increasing attention among researchers and policy makers.[2] Recently, the idea of allowing market forces to discipline large banking organizations, and thus to facilitate the prudential mission of authorities, has known a real boost.

In the US, the financial modernization Gramm–Leach–Bliley Act enacted in November 1999 required a report to Congress on the feasibility of a mandatory policy forcing the largest banks to issue subordinated debt (Subordinated Debt Policy or SDP). Meanwhile, Top 50 national charter banks insured by the FDIC are obliged to have at least one debt issue "A" rated by a specialized agency. The conclusion of this report, conducted by the Fed's Board of Governors and the Treasury Department, was that additional evidence must be gathered before they can support a request for legislative authority to implement a mandatory SDP in the US (see BGFRS&TD, 2000). The report calls for continued research on this topic and encourages the use of market information derived from voluntary sub-debt issues in banking supervision. From an international perspective, "market discipline" is one of the three pillars on which the reform of the Cooke ratio is founded.[3] However, the third pillar of Basel 2 is exclusively focused on the information disclosure process and remains silent about the ways market discipline might strengthen bank regulation and supervision.

In our view, the subordinated debt approach is a more precise alternative to the third pillar of Basel 2. A Sub-Debt Policy defines a concrete disciplinary source, as well as realistic transmission channels in the banking industry (see BGFRS, 1999). Firstly, a *direct*

[1] Federal Deposit Insurance Corporation (FDIC) is the government body charged with the deposit insurance in the United States.

[2] For an excellent survey of the various sub-debt proposals, the reader can refer to BGFRS (1999, Table 1, pp.6–12), BGFRS&TD (2000, Appendix A, pp.58–65) or Evanoff and Wall (2000, p.67 *et passim*). Bliss (2001) and Hamalainen et al. (2005) provide a comprehensive analysis of the theory underlying market discipline in banking and highlight the multi-dimensional structure of the phenomenon.

[3] The other two pillars are: (I) the bank capital regulation and (II) the supervision process. As far as we know, the only theoretical paper which studies the articulation between the three pillars of the New Capital Accord (Basel 2) is that of Rochet (2004). Yet, when the author formalizes the third pillar, he focuses on a Sub-Debt type Policy and not on public disclosure requirements as the Committee does.

channel could be activated *via* the cost of issuing, which theoretically should be sensitive to a change in the bank risk profile. Thus, the appropriate pricing of bank risk in the *primary* market could dissuade (*ex-ante*) banking organizations from adopting chancy activities. Secondly, an *indirect* channel can be effective as long as the supervisor and other private counterparts observe the *secondary* market prices and infer reliable signals concerning the default probabilities of issuing banks. For example, the supervisor may use this alternative source of information (along with other public and/or private sources) when triggering Prompt Corrective Actions, setting up risk-adjusted deposits insurance premia or allocating scarce resources. From this perspective, the market is like an enormous alembic where information, expectations, beliefs, and fears of investors are "distilled" and finally reflected in securities prices. However, the price formation alchemy is very complex and somewhat mysterious: besides default and recovery risks, the secondary market prices of bank debt are subject to the influence of many other non-credit-related factors (e.g. liquidity, taxes, systematic risk factors, and specific features of securities).

For the indirect channel of market discipline to be effective, a necessary (albeit non-sufficient) condition is that the secondary market prices be sensitive to bank risk. That is what we call the "*sine qua non*" hypothesis. The analysis reported in this paper is based on a unique dataset comprising secondary market yield spreads, credit ratings and various accounting measures of bank risk relative to a sample of large European banking organizations observed during the 1995–2002 period. Our main objective is to empirically test the "*sine qua non*" hypothesis of market discipline in the European banking sector.

The main reason motivating our study regards a striking fact mentioned in a recent report made by the Basel Committee (2003). More precisely, it is pointed out that the size of bank sub-debt markets (and, consequently, their underlying disciplinary potential) on the one hand, and the research conducted on these various markets on the other hand, are extremely asymmetric. For instance, if one considers the euro area as a single integrated market, then the European sub-debt market is actually up to twice as large as the US market. As far as research activity is concerned, the vast majority of empirical studies are based on US data, the European markets being practically neglected. As the Committee underlines in its report, "[...] *there seems to be considerable scope and need for examining market discipline outside the US*" (Basel Committee, 2003, p. 12). Indeed, while the US authorities paid a lot of attention to this kind of reform proposals (see e.g. BGFRS, 1999; BGFRS&TD, 2000), the European counterparts have not yet given any serious answer. The absence of theoretical, and especially empirical studies on European data, could explain to a certain extent this curious silence.

The rest of the paper is organized as follows. Section 2 provides a more detailed picture of the indirect channel of market discipline and outlines the various attempts to empirically test its potential effectiveness. Section 3 describes the data sources and sample construction, while Section 4 presents the research methodology. The main results concerning the spreads sensitivity to credit ratings and various accounting measures of bank risk, as well as the robustness checks, are presented in Section 5. Finally, Section 6 concludes and discusses

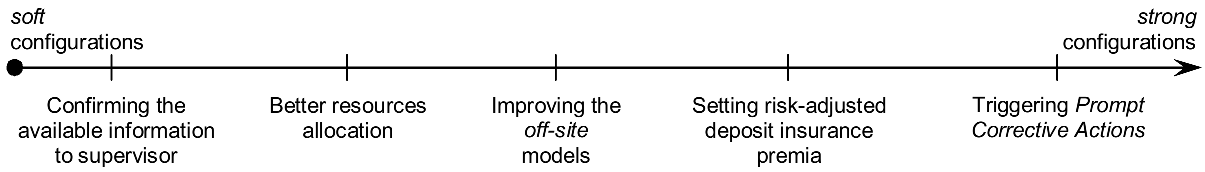

Figure 1: Various configurations of the indirect channel of market discipline.

some policy implications.

2. The indirect channel of market discipline: mechanics and related literature

The logic behind the indirect channel of market discipline presumes that the pricing of bank debt in the *secondary* market, if accurate, conveys to supervisor and other market participants a reliable signal of bank's financial conditions and default risk.[4] On the one hand, the market's reaction could make the bank financing costs rise or bound the business opportunities of riskier banks (e.g. syndicated loans, hedging in OTC markets, credit derivatives). On the other hand, the supervisor could exploit in different ways the market information, available at a reasonably low cost. As there is no clear consensus among researchers around the exact meaning of the indirect channel of market discipline, we offer here a broader definition, which includes several possible configurations (see Fig. 1). In order to discriminate among these multiple configurations, the supervisor may use some of the following criteria: the reliability of market data gathering process, accuracy of market signals, liquidity, market development, experience acquisition for data valuation.

Among the soft forms of the indirect channel we mention the informal treatment of market information in order to refine the supervisor's opinion on sound banks or to justify its doubts about unhealthy ones. To improve the allocation of its scarce resources, the supervisor could schedule more intensive *on-site* examinations primarily on the institutions revealed by the market as being excessively risky. Knowing that the exam frequency is rather rare and that supervisor's private information often becomes obsolete quickly (see e.g. DeYoung et al., 2001), alternative sources of information (such as bank security prices) are likely to have significant practical value. Besides the *on-site* examinations, the bank monitoring device also comprises *off-site* surveillance models, which aim at forecasting either the failure probability or the supervisory internal ratings. The information revealed in real time by the bank debt market could improve the accuracy of such models (see Flannery, 2001).

The strong configurations of the indirect channel formally incorporate market signals

[4] Mitsuhiro Fukao (*Japanese Shadow Financial Regulatory Committee*) named sub-debt "canary bonds," thinking of the canaries used in the past by the mineworkers in search for coal, to warn them about harmful noxes of methane gas (see *Euromoney*, April 2000, pp. 144–146). *Mutatis mutandis*, the market – as the canaries – warns the supervisor and other market participants of a possible financial distress when spreads reach levels comparable to those of junk bonds.

into the regulation and supervision of banks. The use of debt market signals in triggering Prompt Corrective Actions by the supervisor undoubtedly represents the most ambitious form of the indirect channel. The defenders of this configuration (e.g. Calomiris, 1999; Evanoff and Wall, 2000) emphasize an innovative role for market discipline: imposing clear limits to the discretionary behavior of authorities. Regulatory forbearance in the resolution of problem institutions has had disastrous consequences during the virulent banking crises occurred over the past two decades or so (see e.g. Rochet, forthcoming). Hence, strict rules governing the behavior of bank regulators and supervisors based either on spreads or on the ability to issue debt securities would improve the resolution of problem banks while reducing social costs. However, such a configuration of the indirect channel necessitates the existence of strongly efficient markets, able to generate very precise early-warning signals relative to the quality of issuing banks.

In order to assess the disciplinary potential of the bank debt market, some previous papers, including *inter alia* Avery et al. (1988), Gorton and Santomero (1990), Flannery and Sorescu (1996), Evanoff and Wall (2001, 2002), Morgan and Stiroh (2001), Jagtiani et al. (2002), Covitz et al. (2004), Santos (2004), Krishnan et al. (2005, 2006), Evanoff et al. (2008), attempted to determine the extent to which (*primary* and *secondary* market) spreads accurately reflect issuers' financial conditions. Reviewing these studies, which are all concentrated on the US bond market, is beyond our purpose.[5] Rather, in what follows we decided to focus our literature review on the European evidence.

The empirical literature on the presence of market discipline in the European banking sector is quite thin, compared with the US evidence. Bruni and Paternò (1995) show a certain sensitivity of yields to the Moody's rating of European bank issuers, financial leverage, and return on assets. However, the scope of their analysis is very limited: their sample includes only 28 bonds for which the secondary market prices were collected at the end of a single trading day (June 29, 1993).

Sironi (2003) is the first paper to provide a comprehensive analysis of the determinants of *at-issue* yield spreads of large European banks' subordinated debt. Sironi finds that (1) debtholders do discriminate in a rational manner between the different risk profiles of issuing banks;[6] (2) public banks enjoy a significant government subsidy in the form of a lower funding cost; and (3) the risk sensitivity of primary market spreads has been increasing over the 1990s, suggesting that conjectural governmental guarantees vanished during the second part of the decade.

A different empirical approach was adopted by Gropp et al. (2006), in order to take into account the peculiarity of the European banking sector, where public authorities have

[5] These studies generally confirm that the private monitoring is effective in the US bank debt markets. Indeed, market prices reflect quite well the conditions of issuing banks and this information is not redundant with regard to that possessed by the supervisor. See BGFRS (1999), Flannery (1998, 2001), Evanoff and Wall (2000), and Flannery and Nikolova (2004) for comprehensive surveys of this vast empirical literature.

[6] The bank risk profile is proxied by (*i*) the issue(r) ratings; (*ii*) financial strength ratings, which do not take into account any external support from state authorities or bank shareholders; and (*iii*) various accounting variables that previous studies on US data have shown to be relevant in explaining yield spreads.

constantly bailed out the problem banks. The idea is to estimate the ability of market prices to anticipate a "substantial" downgrading (i.e. below "C") of the Fitch–IBCA Individual rating, which eliminates the safety net effect. Such a downgrade is associated to bank fragility. Their results show that spreads are reliable early-warning signals only shortly before the rating downgrade. On the contrary, the *distance to default* (a risk indicator derived from equity prices) is noisy less than 3 months before the rating change, but conveys useful information 6–18 months in advance.

The brief discussion of the studies performed on European data suggests that our paper is most closely related to Sironi (2003). However, Sironi focuses exclusively on primary market prices, which rather pertain to the *direct* channel of market discipline.[7] As the prices formed in the primary market are available to the supervisor only at precise moments in time (the issue dates) and banks do not issue very often *new* debt securities, the primary market is likely to be a weak source of *indirect* market discipline.[8] Moreover, as Covitz et al. (2004) and Covitz and Harrison (2004) convincingly argue, the decision to issue subordinated debt tends to be *endogenous*: banks confronting financial distress have a higher probability of not issuing *new* debt securities. Hence, the risk indicators derived from primary market prices (e.g. *at-issue* spreads) are in fact *unobservable* at the very junctures when they would have the largest potential value for supervisor. These authors also suggest that the results reported in previous studies based on *primary* market spreads may suffer from *sample selection bias*.[9] It is worth noting that this potential econometric problem affects to a lesser extent the empirical studies on market discipline using *secondary* market data.

In a recent article, Evanoff et al. (2008) argue that the information flow is richer and thus banks may be less "opaque" around the time they approach the primary market for new debt placements. To put it another way, banks tend to disclose additional information to investors in order to convince them to accept the new debt issues at competitive prices. By contrast, in the absence of newsworthy events, less information will typically be disclosed on a continuing basis to secondary-market investors. According to this line of reasoning, one might expect that the link between spreads and various proxies for bank risk would be weaker in the secondary than in the primary bond market. In other words, the fact that *primary* market spreads accurately reflect bank risk – as has been shown by Sironi (2003) – does not necessarily mean that the private monitoring performed on an on-going basis by debtholders automatically translates into reliable yield spreads in the *secondary* bond

[7] His argument is that the secondary market is too illiquid to yield reliable bond prices and even the indicative quotes are not very informative (see Sironi, 2001, pp. 249–250). By contrast, at-issue spreads are necessarily based on actual transactions, and not estimated from pricing matrices or dealer quotes.

[8] On average the largest European banks issue subordinated debt 1.5 times a year; the average value ranges form a minimum of 0.5 (i.e. one issue every two years) to a maximum of four times a year (see BIS, 2003; Sironi, 2001). Some of the arguments in favor of using *secondary* market data for supervisory purposes that we discuss in this section are also reviewed in Pop (2006).

[9] By using a dataset comprising large US banking organizations, Covitz et al. (2004) show that the sign and significance of parameter estimates that do not correct for sample selection bias can be seriously misleading.

market. As Morgan and Stiroh (2001) elegantly point out, "*neither market* [primary or secondary] *is obviously the better laboratory, so it seems advisable to have results from both*" (p. 196, emphasis added). In contrast to Sironi (2003), the current paper places more emphasis on the *indirect* (rather than on the *direct*) channel of market discipline and reveals that available prices from the *secondary* market *do* contain information about bank risk.

By studying initial (as opposed to secondary) spreads, Sironi (2003) and other empirical studies using *primary* market data are of great value when assessing the feasibility of SDP proposals. Indeed, as mandatory issuance would certainly occur in the *primary* market, the results reported in these studies are particularly relevant for the debate around the adoption of a SDP. However, it is worth noting that currently there is no sub-debt requirement in place and it is difficult to imagine a scenario in which a SDP will be adopted in the near future by the European countries.[10] Rather, European bank regulators and supervisors seem to favor somewhat less ambitious configurations of *indirect* market discipline, such as the use of market signals to identify weak banks and to complement the traditional sources of information (see e.g. Persson and Blåvarg, 2003; ECB, 2004; Birchler and Facchinetti, 2006). Our study is more in line with these new trends in the regulatory policy arena and market discipline debate.

3. Data sources and sample construction

To study the efficiency of price formation in the European secondary bank debt market, we focus on the relationship between the credit spread and the various measures of bank risk. Our dataset is built using two main sources: *Fitch–IBCA BankScope* for balance-sheet data and bank ratings and *Datastream Thomson Financial* for market data.

We began by identifying from *Datastream* all the issues of fixed-income securities "alive" at the end of 2002 made by European banks (on the whole more than 4,400 issues). Detailed information about issue date, redemption date, amount issued, coupon, amortization features, guarantees, optional features, etc. were collected for each of these issues. Following Jagtiani et al. (2002), we selected one representative security for each banking organization. To be included in the final sample, the selected issues had to satisfy several criteria: (1) publicly traded in a secondary market; (2) no specific option features (put, call, convertibility, etc.) attached to the issues; (3) fixed coupon rate; (4) *in fine* amortization schedule; (5) maturity date after December 31st, 2002.

Selecting only "plain vanilla" (i.e. common) fixed-rate bonds is justified by two distinct reasons (see also Jagtiani et al., 2002). First, the selected issues are rather homogeneous and consequently more comparable according to credit risk related factors. Second, we eliminate the additional noise specific to the binding hypotheses backing the option-adjusted spread calculations. Such models were estimated *inter alia* by Avery et al. (1988) and Flannery and Sorescu (1996).

[10] Even in the US, where such proposals have received extensive support and the bank sub-debt markets are deeper than elsewhere, a SDP has quite small chances to be enacted. In a recent article, Calomiris (2006) contends that the Fed decided to "kill" the SDP proposal, due to opposition from the large US banks.

If several issues made by the same bank fulfilled our eligibility criteria, we preferred those (*i*) that were made before 1995 (to have enough data), (*ii*) whose amount was the largest one (to reduce the size of liquidity premium) and (*iii*) that were subordinated. For the 70 selected issues, 32 being subordinated, we collected the secondary market prices on December 31st over the period from 1995 through 2002.

Once the issuers were identified, we added to our initial dataset their credit ratings and other accounting items (consolidated figures) reported in *BankScope*. Because not all banks had outstanding debt securities at the end of each year of the analyzed period, we assembled an unbalanced sample including 521 observations (bank-year). It is worth noting that our final sample is comparable in size to those used by Flannery and Sorescu (1996, 83 issuers) and Jagtiani et al. (2002, 58 issuers).

4. Model specification and research methodology

If investors' monitoring is effective, it has to be reflected in the prices formed in both the primary and secondary market. The spreads sensitivity to bank risk, as we have already argued, limits the possible configurations of the indirect channel of market discipline. In this context, the "*sine qua non*" hypothesis can be expressed as follows:

> H: "*The investors' monitoring enhances the information relative to financial conditions, risk profile and economic perspectives of bank issuers. This relevant information is incorporated into the spreads, which become sensitive to bank risk and thus likely to be used for supervisory purposes*".

Before we discuss the model specification at greater length, one important caveat about the main hypothesis to be tested, H_1, is worth mentioning. In particular, validating the "*sine qua non*" hypothesis is obviously not enough to prove the effectiveness of market discipline in the European banking sector. Indeed, nothing guarantees that the bank manager's decisions will respond to investors' expectations (see Bliss and Flannery, 2002, for a more refined distinction between *monitoring* and *influencing*). On the other hand, by rejecting this hypothesis, we are able to certify the total failure of the indirect channel of market discipline in Europe.

Following Sironi (2003) and Flannery and Sorescu (1996), the general framework of our analysis is based on the functional relation between the yield spread and various measures of bank risk:

$$\text{SPREAD}_{it} = f\left(X_{it}, Y_{it}, Z_{it}\right) + \epsilon_{it}, i = \overline{1,70}, t = \overline{1995,2002} \quad (1)$$

SPREAD_{it} = the difference between the bank bond yield to maturity and the yield of a corresponding currency Treasury security;

X_{it} = market measures of bank risk;

Y_{it} = accounting measures of bank risk;

Z_{it} = other control variables likely to affect SPREAD_{it}

The linear form of the function $f(\cdot,\cdot,\cdot)$, also used in some other previous studies, can be viewed as an approximation, more or less accurate, of the SPREAD/risk relationship:[11]

$$\text{SPREAD}_{it} = \alpha + \beta X_{it} + \sum_{k=1}^{K} \xi_k Y_{kit} + \sum_{j=1}^{J} \psi_j Z_{jit} + \epsilon_{it} \tag{2}$$

As far as the construction of the dependent variable is concerned, we used a method similar to that of actuarial spread, which is the common reference among market professionals. The construction of this type of spread presupposes the choice of a benchmark Treasury security denominated in the same currency and having a maturity similar to that of the risky bond. When there is no benchmark of the same maturity, most authors (Jagtiani et al., 2002; Sironi, 2003, *inter alia*) use linear interpolations. In contrast to these studies, we use an alternative measure of actuarial spread, which integrates all the information contained in the risk-free yield curve. Initially, we built the risk-free term structure from a panel of Treasury securities (like OAT and BTAN for France, BUNDS and BOBL for Germany, etc.).[12] Then, we calculated the yields on each bank debt issue using the market gross prices (including the accrued interest) collected at the end of each year between 1995 and 2002.[13,14] The benchmark yield is estimated by substituting the bank debt maturity in the cubic equation that describes the risk-free yield curve of the corresponding sovereign issuer. Finally, the difference between the two yields defines our dependent variable SPREAD_{it} (expressed in percentage) for each bank issuer at the end of each year of the analyzed period.

The data concerning the SPREAD variable are presented in Table 1. The level of spreads, relatively low (0.6% on average) at the beginning of the analyzed period (1995–1997), has increased since 1998 (at about 1% on average). The fourth column of the same table exhibits similar patterns for the SPREAD volatility. The standard deviation of SPREAD had gradually increased from 0.35% in 1995 to more than 1% in 2002. The interquartile range ($Q_3 - Q_1$), a variability measure less sensitive to extreme values, had a similar evolution

[11] The samples constructed by Avery et al. (1988), Gorton and Santomero (1990), and Flannery and Sorescu (1996) exhibit a (quasi-)linear relation between SPREAD and bank assets risk. However, Jagtiani et al. (2002) show that, in the case of undercapitalized banks, SPREAD increases faster with risk.

[12] The risk-free yield curves were estimated for seven different sovereign issuers (*viz.* France, Germany, Italy, the Netherlands, Switzerland, the United Kingdom, and the United States) according to the currency in which the bank debt issue was denominated. Estimation details for best fit calculations of benchmark yield curves are presented in Appendix 1.

[13] The market price is the latest price obtained from the market, quoted either as a clean or gross price, depending on local market practices. For some markets, this is the current real-time price; for others, it is last night's closing price. It is always a mid-price. Certain data providers (e.g. *Bloomberg*) report "indicative" quotes or "predicted" (matrix/BGN) prices, which are not necessarily based on actual trades. However, private correspondences with the team *Datastream* (London) confirmed us that all the prices used in our study always correspond to actual trades.

[14] The accrued interest is calculated according to conventions governing each market. The yields calculations depend on the practices specific to each market, e.g. semi-annually in the US Treasury market and annually in the Eurobonds market.

over the considered period. The highest spreads, recorded at the end of 1998, were most probably caused by the Russian default of August 1998, which seriously impaired the pricing in the bank debt market both in the United States and Europe (see Hancock and Kwast, 2001; Sironi, 2001).

{Table 1 about here}

The distribution of SPREAD by country, depicted in Table 2 (columns 3&4), reveals some interesting aspects concerning the potentially asymmetric transmission of market discipline in the European banking sector. Firstly, German, Austrian and French banks have lower spreads (0.59%, 0.59%, and 0.75% respectively) than the European average (0.87%). This stylized fact could be explained by, among other things, the larger shares held by the public-sector banks in these countries. Secondly, the UK, Spanish, Italian, and Swedish bank bonds exhibit above European average spreads. Sironi (2003) also finds that German/UK banks pay spreads significantly lower/higher on the *primary* market with regard to their European competitors.

{Table 2 about here}

The market measures of bank risk (X_{it}) used in this study are the traditional credit ratings and the financial strength ratings assigned exclusively to banks.[15] Because no data on specific bank debt issue ratings was available, we used the issuer ratings attributed by the most active international agencies (Standard and Poor's, Moody's, and Fitch–IBCA) instead. The three agencies use relatively similar scales and criteria, and assign rather comparable ratings. The Pearson correlation coefficients between the various credit ratings are all positive and strongly significant. Furthermore, differences higher than one notch are observed only in one of ten cases when two rating agencies rated the same issuer. The ratings are converted to cardinal values according to the scale presented in Appendix 2. A lower cardinal value corresponds to a higher credit quality.

Finally, the SP-M-FI$_{it}$ variable is the average of ratings assigned by the three agencies to bank i at the end of year t. The time evolution of this variable, described in Table 1, is less marked than the evolution of SPREAD, reflecting the vision "through the cycle" of rating agencies and their lethargic adjustment behavior. The distribution by country (Table 2) reveals that German banks are better rated (2.71 or AA+/AA1) than the European average (3.81 or AA–/AA3). Moreover, the negative relationship between SPREAD and SP-M-FI is consistent with financial theory (see Table 3, panel A): a lower quality rating corresponds on average to a relatively higher spread, in spite of the fact that interquartile intervals are not always disjoint. The Pearson correlation coefficients between SPREAD and credit ratings are positive and statistically significant at the 1% level.

[15] As investors may have already taken into account credit ratings in pricing bond issues, the spread/rating relationship seems somewhat "tautological." J.-Ch. Rochet has pointed out that we should be interested in more "objective" measures of banking risk, as the financial ratios computed from balance-sheet data (*vide infra* §5.3).

{Table 3 about here}

Although the traditional credit ratings are synthetic market measures of bank solvency, they do not necessarily reflect the genuine risk profile of issuing banks. In the presence of *de jure* (for public-sector banks) or *de facto* (for "too-big-to-fail" banks) governmental guarantees, the capacity of an entity to honor its debt service could be excellent even if its intrinsic financial conditions are poor. The rating agencies have soon recognized this problem and proposed new ratings, focused on the intrinsic safety and soundness of banks, which exclude certain external credit risks and credit support elements addressed by traditional ratings. These ratings can be considered as an objective evaluation of the likelihood that a bank needs to seek an outside support, either from state authorities or its shareholders.

Moody's Bank Financial Strengths (MBFS) and Fitch–IBCA Individual (FII) ratings, both specific to banks, are two examples of such ratings. The Pearson correlation coefficient between the two ratings is about 0.76, whereas differences higher than one notch are recorded more often (in 24% of common ratings) than in the case of traditional ratings. The MBFS-FII continuous variable, representing the average of the two ratings, was computed as in the previous case (i.e. of the SP-M-FI variable).

All banks included in our sample are classified as investment grade (minimum BBB+/Baa1) according to the traditional ratings, but once the influence of the safety net is eliminated (by considering the MBFS-FII ratings), this assignment is no longer valid. Table 3 (panel B) proves the existence of a certain number of D/E+ rated banks that have very poor financial conditions. According to Table 2 (columns 5&6), the larger differences between traditional and financial strength ratings are observed in the case of German and Austrian banks; the French and Italian banks also received better traditional ratings, the difference being a little bit lower. These simple descriptive statistics suggest that the safety net protecting banking systems in these countries are relatively more generous than those adopted in the UK or Switzerland for example.[16]

To explain better the SPREAD variability, we used several accounting measures of bank risk (Y_{kit}), usually employed in the literature, and a whole series of control variables (Z_{jit}) (see Table 4 for a brief description of the main explanatory variables).

{Table 4 about here}

The accounting variables are observed at the end of each year of the 1995–2002 period, for each bank issuer. Yet, the financial statements are publicly disclosed several weeks after the end of the year. So, on the last day of the year (December 31$^{\text{st}}$), the various bank-specific measures of the risk profile (Y_{kit}) are not yet publicly released; they may only be known with some "error." By not taking into account the fact that accounting data are reported with a lag, our tests should be biased against finding a significant relationship between the various financial ratios and spreads. Basically, there are two different methods to deal with this problem of measurement errors in variables. The first one, used by Krishnan et

[16] For Swiss and UK banks, the traditional and MBFS-FII ratings are relatively aligned.

al. (2005), is to employ the standard two-stage least squares procedure. The second one, suggested by Flannery and Sorescu (1996) and Jagtiani et al. (2002), is to compute the SPREAD variable using the market prices observed on January 31st of each following year (i.e. from 1996 through 2003), which post-date the release of financial statements. For simplicity and due to the low (annual) frequency of our accounting variables, we opted for the latter method. Specifically, the main analysis will be done using end-of-January spreads and credit rating data along with year-end accounting data. However, we also estimate the regressions with the spreads observed on December 31st of each year by using both OLS and the two-stage least squares (TSLS) procedure; the results will be discussed as a robustness check.

Descriptive statistics for the main explanatory variables are presented in Table 2. Among the control variables, the issue size is relatively large (US$ 260.17 million, on average), while the average maturity is about 11 years. The vast majority of the issues are international (72%, including Eurobonds). As *Datastream* supplies information concerning the subordination status only for the international issues, we could identify no more than 32 subordinated bonds. Finally, in our sample, about 20% of bank issuers belong to the public sector, benefit from explicit governmental guarantees, or are assigned with a Fitch–IBCA Support rating equal to 1. Most issuers for whom the *Support* variable takes the value of 1 are located in Germany, Austria, and France.

5. Empirical results

5.1. SPREAD *variability and traditional ratings*

Table 5 (columns 1–3) reports the results of OLS pooled regressions when banking risk is proxied by the traditional credit ratings. The coefficient of the rating variable (SP-M-FI) is strongly significant (at the 1% level) and has a positive sign, as expected: the lower the bond rating, the higher the yield spread required by investors. A one-notch credit downgrade implies an increase of the spread by 0.081% (or 8.1 bps) on average.[17]

{Table 5 about here}

The issue size (ln(AISD)) has a negative and statistically significant coefficient, in accordance with financial theory. The amount issued is often associated to indirect measures of the secondary market liquidity. The idea is that smaller issues are likely to be more easily absorbed in investors' portfolios, thus reducing market liquidity (see BGFRS, 1999; Basel Committee, 2003). The maturity of the issue has a positive and significant coefficient, as predicted by financial literature: the default probability is an increasing function of the investment horizon. Surprisingly, the subordinated status of the issue does not seem to be a significant explanatory factor of SPREAD variability.

[17] This elasticity is comparable with that reported by Jagtiani et al. (2002, Table 3, p. 572) on US data, between 1992 and 1997, i.e. of 0.061. As investors may have already taken into account credit ratings in pricing bond issues, the spread/rating relationship seems somewhat "tautological."

The year dummies α_t, $t = \{1998, \ldots, 2002\}$ have positive and significant coefficients, in accordance with the descriptive statistics presented in Table 1. Spreads are on average higher after the market turmoil at the end of 1998, turned on by the Russian default and subsequent financial collapse of Long Term Capital Management. The liquidity crisis has persisted and even reverberated in the aftermath of recent financial scandals and events (e.g. Enron, September 11$^{\text{th}}$). In an alternative specification, we also included the *Recession* dummy to control for the business cycle; the coefficient of this new variable was positive as expected but not significant at conventional confidence levels (unreported result).

Following previous studies showing that split ratings have a significant influence on credit spreads, we added two other variables to our basic empirical model: *Split* and *Split*Recession* (see Table 4, columns 2&3). The coefficients of these new variables are positive and strongly significant suggesting that (1) bank issuers which are rated differently by the two major US agencies have higher spreads and (2) the impact of rating splits is greater in recessions. When the two variables are both included in the empirical model, the *Split* coefficient pales in significance.

Among "country" dummy variables, only *UK* and *Sweden* exhibit significant coefficients. So, the bonds issued by Swedish and British banks are traded on average at spreads higher than those of the other European banks. A clear interpretation of this result is not easy to find. As far as the British banks are concerned, explaining the positive sign of *UK* by invoking only credit quality arguments is obviously not satisfactory.[18] Sironi (2003) puts forward the differences in the perceived safety net and those between business cycle phases in the UK and other continental Europe countries. As agencies tend to value the issuers through the cycle, the assigned ratings do not necessarily reflect the current state of the economic cycle in the issuers' countries. On the other hand, the market being forward looking, it prices the bonds according to the economic conditions and perspectives of the issuer. Consequently, the deterioration of the business environment in the UK relative to the continental Europe could justify the marginal explanatory power of *UK*.[19]

[18] Sironi (2003) and Gropp et al. (2006) also find that British banks' subordinated debt spreads are significantly higher than those of the other European banks.

[19] Mark Flannery suggested an alternative explanation for the fact that, *given everything else*, the spreads of UK banks are found to be higher than those of continental Europe bank issuers. Namely, banks with larger and more active domestic markets (such as UK banks) are more likely to issue in their own national markets (for instance, this is usually the case for large US banking organizations). If continental Europe banks issue debt securities more often *via* their wholly-owned subsidiaries located in "tax heavens," this fact could explain the higher spreads on UK bonds. Sironi (2001, p. 241) reports that 23% of the issues made from 1988 through 2000:Q1 by European banks are completed in this way, simply for the benefit of investors who whish to avoid taxes on interest income. Yet, Sironi does not provide the distribution by country of these "tax havens" issues. In our sample, only 6 continental Europe banks (out of 60) issued bonds through foreign subsidiaries (located in Luxembourg, Curacao, and the Cayman Islands), while none of the UK banks' issues were completed in "tax heavens." Exploring the determinants of this "UK premium" in the secondary bond market is beyond our purpose. However, we consider that this puzzling evidence deserves further investigation.

Adding fixed effects to our initial empirical models leaves the main results basically unchanged (see Table 6, columns 1–3). The coefficient of the SP-M-FI variable is positive and statistically significant at the 1% level, whichever empirical specification is used.

{Table 6 about here}

5.2. *Financial strength ratings as proxies for bank risk*

To ascertain if investors correctly price the intrinsic risk profile of each issuer, we propose an alternative specification by replacing the traditional ratings (SP-M-FI) with the financial strength ratings (MBFS-FII), specific to banks. The results, presented in Table 5 (columns 4–7), strengthen the findings summarized in the previous section. The coefficient of the MBFS-FII ratings is positive and statistically significant at the 1% level. The other control variables (except the *Subordinated* dummy) continue to affect SPREAD as predicted by the theory.

Two additional variables (*TooBigToFail* and *Support*) were included into the specification comprising the MBFS-FII ratings, aiming to control for the conjectural governmental guarantees and bailout policies.[20] The corresponding results are presented in Table 5, columns 6&7. The negative coefficient of *Support*, which is significant at the 1% level, reveals that the debt issued by European public-sector banks is traded at spreads that are relatively low with respect to their intrinsic risk profile. This implicit governmental subsidy, reflected by the decline of spreads, is about 21 bps. Furthermore, the coefficient of *Germany* becomes statistically significant, its negative sign indicating that German banks' bonds exhibit spreads lower than those of European competitors. This result can be explained by the presence of strong governmental guarantees in the German banking sector. To highlight the relevance of this finding, we note the recent conflict between the European Commission and the German *Landesbanks*.[21] The public funds provided by local governments (*Länder*) at below market rates were judged illegal by the Commission. In addition, Germany's powerful *Länder* (states) hold direct stakes in many of the *Landesbanks*, which thus benefit from hypothetically unlimited public guarantees. Thanks to this public shield, the *Landesbanks* are assigned with excellent (top-notch AAA/Aaa) credit ratings, allowing them to raise funds at cheaper rates than their private-sector rivals.[22] Sironi (2003, p. 458) finds a similar result on the *primary* market: the European public-sector banks benefit from subsidies *via* financing cost savings estimated on average at about 40 bps.

[20] We preferred this specification, because unlike the one including the traditional ratings, it does not take into account any external support factors. The distinction between the two effects is not so clear as long as the Fitch–IBCA Support rating, used in the construction of *Support*, already includes "too-big-to-fail" effects.

[21] The *Landesbanks* are public credit institutions providing financial services, like central bank type operations for the local savings banks (*Sparkassen*), housings schemes and industrial start-ups for state governments, and commercial/investment banking operations for private-sector firms. The *Sparkassen* also benefit from explicit governmental guarantees being entirely owned by local municipalities.

[22] This story, related in several issues of *The Economist* (April 15$^{\text{th}}$, 2000; December 9$^{\text{th}}$, 2000; October 19$^{\text{th}}$, 2002), was resumed *inter alia* by Sironi (2003), Basel Committee (2003) and Gropp et al. (2006).

The *within* estimations reported in Table 6 confirm that the MBFS-FII coefficient remains positive and significant at the 1% level, while the *TooBigToFail* and *Support* coefficients are negative and significant as expected.

5.3. *The "accounting" empirical model*

The results of OLS estimations (with or without fixed effects) of the model including accounting variables are reported in Table 7. Generally, the findings in terms of SPREAD sensitivity are less conclusive than those reported in previous sections. So, the measure of bank performance (ROAA) affects SPREAD very weakly, even when interacted with financial leverage (ROAA**Lev*). However, when the coefficients of these variables are significant, the signs are as expected (see columns 1, 2&5). Particularly, the profitability seems to be more valuable in the case of high-leveraged banks. As for the financial leverage, we used two alternative measures. The first one (*Leverage*), calculated directly using balance-sheet data, poorly explains the SPREAD variability. The second measure (*Cooke*) significantly affects the pricing of bank bonds in only one specification (column 4). As long as the Cooke ratio is considered by the supervisor as a trigger for inflicting penalties to under-capitalized banks, our conjecture is that investors are likely to give more importance to this second variable. The percentage of loans in total assets (*NetLoans*) seems not to be a relevant explanatory factor, while the sign of the liquidity risk variable (*Liquidity*) is very sensitive to the adopted specification.

{Table 7 about here}

The various variables quantifying the credit risk (LLR, *BadLoans*, and the corresponding interactive variables) exhibit in most cases significant coefficients. The loan loss reserve is favorably perceived by investors as a supplementary cushion likely to absorb future expected losses on the credit portfolio only in the case of high-leveraged banks. The sign of *BadLoans* is negative, contradicting at first sight the rational pricing hypothesis. However, when this variable interacts with *Leverage*, the influence becomes positive and significant. This result suggests that for under-capitalized banks, a higher non performing loans ratio implies relatively larger spreads, in accordance with a rational pricing.

Clearly, if spreads do reflect bank risk and performance, they are likely to reflect the *net* effect of *all* accounting variables on risk, rather than any accounting variable taken individually. Covitz et al. (2004, p. 82) and Flannery and Sorescu (1996, p. 1361) point out that, as the various accounting measures of bank risk are related to each other, the variances of each of the individual parameter estimates can be misleadingly large. In order to mitigate this potential bias, we performed several tests for the hypothesis that bank-specific variables' coefficients are jointly zero (see the rows corresponding to F^b and F^c-statistics in Table 7). In all but one specification, the bank-specific accounting variables and traditional credit quality measures have significant predictive capability over credit spreads, beyond all other control variables.

Off-balance sheet operations are perceived by the debtholders as risk-reducing banking activities: the OBSA coefficient is negative and significant (columns 3&4). This result is consistent with that obtained by Hassan et al. (1993). Unfortunately, the lack of detailed data in *BankScope* prevented us from leading a more refined analysis, i.e. distinguishing between the various off-balance sheet items (securitizations, stand-by letters of credit, swap operations, etc.).

The control variables previously used, namely ln(AISD), *Maturity*, and *Split*, have a significant influence, consistent with the economic intuition. Interestingly, the *Subordinated* dummy variable exhibits now a positive and significant coefficient, as predicted by financial theory. The "year" dummies confirm once again that spreads had considerably increased after the crisis of autumn 1998. As far as the "country" dummy variables are concerned, we find once again that German banks' bonds are traded at significantly lower spreads (unreported result). Finally, the *TooBigToFail* coefficient becomes statistically significant and negative in the fixed effects specifications (columns 5&6), while *Support* negatively affects SPREAD in all specifications.

In summary, even if the results presented in this section are not as conclusive as those reported in previous sections, we consider that the "*sine qua non*" hypothesis of the indirect channel efficiency cannot be entirely rejected. Before closing this section, we propose two plausible (though not necessarily competing) explanations that could help us understand better the weaknesses of the accounting model compared with the specifications including credit ratings. The first explanation pertains to the reticence of banks to reveal certain sensitive information as loan loss reserves, provisions in the profit and loss account or non performing loans. Indeed, the number of observations decreases sharply (to 224–259) when we take into account the *BadLoans* variable (see columns 3&4), impairing the quality of our estimations.

Second, the accounting standards are different from one country to another, thus decreasing the degree of comparability of our proxies of bank risk and performance. The heterogeneity of accounting definitions is more severe in the case of non performing loans, loan loss reserves, and charge offs. Obviously, the credit ratings do not suffer from this shortcoming. When the ratings are added to the accounting variables, we find that the coefficients of these last ones become insignificant, while ratings continue to exercise a significant influence (omitted output). In addition, in order to control for cross-country differences in accounting standards, we also interacted financial ratios with country dummies (this solution is suggested in Sironi, 2003). However, the results we obtained are not significantly better than those reported in Table 7.

5.4. ***Robustness tests***

This section summarizes the main results of several tests conducted in order to check the robustness of the spread/risk relationship. In particular, we used alternative measures of dependent, control, and independent variables.[23]

One of the difficulties of our study was to compute spreads using a proper benchmark risk-free rate in an integrated market. Consequently, for the issues denominated in euro after 1999, the former risk free rates were replaced with the yields on the Treasury securities issued by AAA rated European sovereigns (in particular Germany, Austria, France, and the Netherlands). Also, the risk-free interest rates used in SPREAD computations were computed from benchmark yield curves estimated by a 5^{th} order polynomial equation (see Appendix 1). The results of our estimations are not sensitive to these various SPREAD measures.

As we have already mentioned in Section 4, by regressing the end-of-December spreads on variables depicting the end-year financial conditions (but revealed a couple of weeks later), one supposes implicitly that accounting information is incorporated in market prices observed on December 31^{st}. This binding hypothesis would imply the acceptance of the strong form of market efficiency (see Flannery and Sorescu, 1996). Since one of the objectives of the paper is to test whether accounting data is correlated with spreads, the main analysis reported in §5.3 has been done using market prices observed at the end of January, when the accounting information is publicly known. However, as a robustness check, we also estimated the "accounting" empirical model with the spreads observed on December 31^{st} of each year. The results (not included here for space reasons) are qualitatively similar to those reported in Table 7.

In addition, following Krishnan et al. (2005), we also used the standard two-stage least squares procedure in order to deal with the problem of measurement errors in variables. Specifically, the bank-specific (accounting) variables are instrumented by the control variables, lagged accounting variables, and SPREAD_{t-1}. To determine the marginal contribution of each block of explanatory variables (controls and bank-specific variables, respectively), we conducted several F-tests. Table 8 shows the partial F-statistics, the associated p-values (in parentheses) for each of the two blocks of independent variables, and the adjusted R^2 values, separately for three empirical models: Model 1 including the control variables, as well as *Leverage* (specification A) or *Cooke* (specification B), ROAA, ROAA**Lev*, *NetLoans*, and *Liquidity*; Model 2 including the credit-quality measures LLR, LLR**Lev* in addition to all the explanatory variables included in Model 1; and Model 3 or the "full" model including two other credit-quality measures (*BadLoans* and *BadLoans*Lev*) in addition to all the explanatory variables included in Model 2. Again, the results confirm our "*sine qua non*" hypothesis: the block of bank-specific variables is important in explaining credit spread levels.

{Table 8 about here}

By substituting the control variable ln(AISD) with bond *Age* as a proxy for the liquidity premium and changing the definition of the *TooBigToFail* variable (by considering the ratios

[23] For space reasons, we do not report all the robustness tests described in this section. However, the results are available upon request.

of $\text{TA}_{it}/\text{avg.}\{\text{TA}_t\}$ or $\text{TA}_{it}/\max\{\text{TA}_{country}\}$), our former results remain basically the same. An interesting result, which is worth mentioning, is that the oldest – *off the run* – issues exhibit higher liquidity premia and consequently higher spreads.

To mitigate the drawback related to credit ratings cardinalization (implicitly assuming a linear relation between ratings and bank solvency), we replaced the continuous variables SP-M-FI by dummies for each rating class: $\Re_j \in \{\Re_1, \Re_2, \ldots, \Re_8\}$, where $\Re_1$ represents the AAA/Aaa class and $\Re_8$ the BBB+/Baa1 class (i.e. the worst in our sample). By definition, $\Re_j = 1$ if the rating belongs to the class j and 0 otherwise. The best class (AAA/Aaa) dummy variable was dropped in order to avoid multi-collinearity (see also Sironi, 2003). The sensitivity of SPREAD to credit ratings is once again confirmed:[24]

$$\text{SPREAD}_{it} = \alpha_i + \underset{(0.06)}{\underset{0.01}{\xi_2}}\Re_{2it} + \underset{(1.99)}{\underset{0.27^{**}}{\xi_3}}\Re_{3it} + \underset{(2.82)}{\underset{0.37^{***}}{\xi_4}}\Re_{4it} + \underset{(2.83)}{\underset{0.57^{***}}{\xi_5}}\Re_{5it} + \underset{(3.62)}{\underset{0.90^{***}}{\xi_6}}\Re_{6it} + \underset{(3.13)}{\underset{0.73^{***}}{\xi_7}}\Re_{7it} + \underset{(3.51)}{\underset{1.16^{***}}{\xi_8}}\Re_{8it} + \gamma Z_{it} + \epsilon_{it} \quad (3)$$

where Z is a vector of control variables and ***, ** indicate statistical significance at the 1%, 5% level respectively. Heteroskedasticity-consistent t-statistics are reported in parenthesis below each coefficient estimates. The null hypothesis that all coefficients on the subset of rating dummy variables ($\Re_2, \ldots, \Re_8$) jointly equal zero is rejected at reasonable confidence levels: (*i*) *pooled* model $F = 17.61$, $\chi 2 = 123.26$, $p < 0.01$; (*ii*) *fixed effects* model $F = 3.33$, $\chi 2 = 23.33$, $p < 0.01$. Furthermore, these coefficients are positive and generally statistically significant, ranking according to the considered rating classes: $\widehat{\xi}_2 < \widehat{\xi}_3 < ... < \widehat{\xi}_8$.

Instead of return on assets (ROAA), the bank performance was expressed by three other measures: return on equity, net interest margin, and net interest income/average assets ratio. Also, the financial leverage (*Leverage*) was proxied by the following alternative variables: equity/liabilities, equity/total assets, capital funds/liabilities, and capital funds/total assets. Instead of the Cooke ratio (*Cooke*), we used the tier one ratio. As a proxy for the liquidity risk, we also employed the liquid assets/customer and short-term funds ratio. The results obtained with these various alternative measures of bank risk and performance do not outperform the quality of our initial specifications reported in Table 7.

In order to detect certain particular patterns in SPREAD sensitivity to credit ratings and various accounting variables, the analyzed period was split in four different sub-periods: 1995–1996, 1997–1998, 1999–2000, and 2001–2002.[25] The results obtained for each of these sub-periods confirm that SPREAD is sensitive to both traditional and financial strength ratings (unreported result). With one exception (1999–2000), the SP-M-FI variable has a positive and statistically significant coefficient. Furthermore, this sensitivity appears to be higher at the beginning (0.108 at the 1% level) and at the end (0.118 at the 5% level) of the analyzed period. The coefficient of MBFS-FII has the highest significance between 1995

[24] We replicated the same empirical exercise for the financial strength ratings, MBFS-FII. The results are quite similar but not as strong.

[25] We also attempted to perform estimations for each year between 1995 and 2002, but the results were less conclusive in particular because of the reduced number of observations (40 on average) coupled with the relatively large number of independent variables.

and 1996 (0.057 at the 1% level). The control variables significantly affect SPREAD in the right direction. Again, the debt issued by public-sector banks and by banks benefiting from explicit guarantees (either from the state authorities or their shareholders) is traded at spreads substantially lower than those of private-sector banks. The coefficient of *Support* has a negative sign regardless of the considered sub-period; the marginal influence of this variable turns out to be stronger between 2001 and 2002.

By regressing SPREAD on the accounting measures of bank risk and performance we obtain mixed results (omitted output). The capital adequacy ratio exhibits a negative and significant coefficient over the 1995–1996 and 2001–2002 periods. The credit-quality measures enter significantly after 1997. The same result holds for the bonds issued by public-sector banks: the sign of *Support* is negative, as expected, over all sub-periods, but is significant only after 1997. According to these results, the pricing in the secondary debt market is relatively more sensitive to bank risk profile in the second part of the analyzed period. However, as pointed out by Sironi (2003), it is difficult to track down specific turning points in the evolution of the SPREAD sensitivity in the European bank debt market. Indeed, no spectacular regulatory change – comparable to the adoption of FDICIA in 1991 in the U.S. for example – took place in Europe between 1995 and 2002.

6. Conclusions and policy implications

This article complements the plethora of empirical studies performed mainly on US data with a comprehensive analysis of the secondary market prices sensitivity to the risk profiles of the largest European issuing banks. More precisely, our objective was to empirically test the "*sine qua non*" hypothesis of the indirect channel effectiveness. This hypothesis postulates that investors' monitoring translates into the production of relevant information about the financial conditions and perspectives of issuing banks.

This hypothesis was tested by modeling the yield spread between the market interest rate on option-free bonds issued by banks and the corresponding risk-free rate of the same maturity as a function of various bank risk measures. On the whole, our results suggest that credit spreads are sensitive to the financial conditions and risk profiles of bank issuers, as reflected in traditional credit ratings and especially Moody's Bank Financial Strength and Fitch–IBCA Individual ratings, assigned only to financial firms. These last ratings are more accurate risk measures as long as they exclude the effects associated with the safety net, symptomatic for the banking industry. However, the relation between the spreads and various accounting measures of bank risk and performance is weaker, in particular because of the heterogeneity of the accounting standards applied in European countries.

All in all, secondary market spreads *do* contain valuable information about the financial conditions and risk profile of bank issuers and hence should not be ignored by the decision-makers responsible for banking regulation and supervision in Europe. It is worth emphasizing that validating the "*sine qua non*" hypothesis can neither serve to justify the SDP proposals nor prove the effectiveness of market discipline in the European banking sector. Indeed, nothing guarantees that banks react to signals sent by the market in order to align their strategies with the interests of investors. On the other hand, by accepting it, at least we can reject the failure of the indirect channel in Europe.

Finally, our results concerning the government-owned banks or banks protected by explicit guarantees cast some doubts on the disciplinary role of the bond market in this particular case. In certain European countries, the public-sector banks – often the inefficient ones – enjoy a hypothetically unlimited governmental guarantee, which may hinder competition not only at national level, but also at international level. Furthermore, for these banks the indirect channel of market discipline is, *a priori*, ineffective. The bailout of inefficient banks, confronting or not financial distress, even if it is favorably perceived in the short run from a strictly political point of view, may turn out in a long-term to be a losing strategy. Indeed, one of the surest modes to weaken modern banking systems is to tolerate abusive bailout policies and hence to obstruct the various channels of market discipline transmission mechanism. In order to better assess the asymmetric transmission of market discipline, especially in the case of systemically important financial institutions, a worldwide comparison of spread sensitivity to bank risk may be an interesting avenue for further research.

One potential advantage in using secondary (rather than primary) market prices to monitor bank risk is that at a given point in time they can be observed for multiple bonds of the same issuer and that they are available at a very high frequency. This greater flexibility of the secondary market data could be exploited in the European context by constructing the entire shape of the term structure of credit spreads, as has been done by Krishnan et al. (2005, 2006) on US data, and by studying the informational content of the slope of credit-spread curves.

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Appendix 1. Least squares polynomial method of best fit calculations for benchmark yield curves

This appendix contains the calculations for the least squares polynomial method of best fit used to plot benchmark yield curves stored in *Datastream*. The formulae describe the mathematical derivation of a polynomial equation as best fit to a series of data-points expressed as co-ordinates $(X_i,\, Y_i)$, $i = \overline{1, n}$.

The equation of the curve is:

$Y = a + bX + cX^2 + dX^3 + \epsilon$.

To fit a polynomial curve to the points, the standard method of least squares curve fitting is used. In this manner, the differences between the observed values of X and Y and the curve are minimized. Using this method, the values that determine the shape of the curve (a, b, c, and d) are found by solving the following linear simultaneous equations:

$\sum_{i=1}^{n} Y_i = na + b\sum_{i=1}^{n} X_i + c\sum_{i=1}^{n} X_i^2 + d\sum_{i=1}^{n} X_i^3$

$\sum_{i=1}^{n} Y_i X_i = a\sum_{i=1}^{n} X_i + b\sum_{i=1}^{n} X_i^2 + c\sum_{i=1}^{n} X_i^3 + d\sum_{i=1}^{n} X_i^4$

$\sum_{i=1}^{n} Y_i X_i^2 = a\sum_{i=1}^{n} X_i^2 + b\sum_{i=1}^{n} X_i^3 + c\sum_{i=1}^{n} X_i^4 + d\sum_{i=1}^{n} X_i^5$

$\sum_{i=1}^{n} Y_i X_i^3 = a\sum_{i=1}^{n} X_i^3 + b\sum_{i=1}^{n} X_i^4 + c\sum_{i=1}^{n} X_i^5 + d\sum_{i=1}^{n} X_i^6$

Where Y_i = observation of the "redemption yield" for a treasury security in list;

X_i = observation of the "life" for a corresponding treasury security in list;

n = number of treasury securities in list.

These equations are solved using matrix reduction techniques to provide values for a, b, c, and d. The situation above describes the derivation of the equation of a curve in the 3rd power of X. For each market, two types of benchmark yield curve are calculated: to the power of 3 and to the power of 5. A better fit is achieved as the squared multiple correlation coefficient (R^2) approaches 1.

Notes:

1° Yield curves of France government contain 3-month money market rates in order to stabilize the short end of the yield curve.

2° Values for spreads do not include bonds that are perpetual or whose life exceeds the maturity value range for the market (i.e. [0.8–12] for Germany, Italy, the Netherlands, Switzerland, and [0.8–32] for the US, France, the UK). To do so would produce meaningless spread values through extrapolation.

Appendix 2. Ratings scales

a) Traditional credit ratings

Cardinal value	1	2	3	4	5	6	7	8	9	10	11	12	13	14
S&P	AAA	AA+	AA	AA−	A+	A	A−	BBB+	BBB	BBB−	BB+	BB	BB−	B+
Moody's	Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3	Ba1	Ba2	Ba3	B1
Fitch	AAA	AA+	AA	AA−	A+	A	A−	BBB+	BBB	BBB−	BB+	BB	BB−	B+

b) Financial strength ratings

Cardinal value	1	2	3	4	5	6	7	8	9	10	11	12	13	14
MBFS	A	A−	B+	B	B−	C+	C	C−	D+	D	D−	E+	E	E−

Cardinal value	1	2.5	4	5.5	7	8.5	10	11.5	13	–
FII	A	A/B	B	B/C	C	C/D	D	D/E	E	–

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Table 1
SPREAD and Ratings -- Distribution by Year

	SPREAD[a] (%)			SP-M-FI[b]			MBFS-FII[c]		
Year	*N*	Mean	Std. dev.	*N*	Mean	Std. dev.	*N*	Mean	Std. dev.
1995	50	0.544	0.352	47	3.68	1.83	33	4.27	2.14
1996	56	0.641	0.524	48	3.70	1.90	39	4.15	2.10
1997	65	0.745	0.724	52	3.71	1.86	41	4.34	2.12
1998	70	1.032	0.976	53	3.68	1.69	48	4.78	2.19
1999	70	0.903	0.832	55	3.74	1.60	51	4.85	2.05
2000	70	0.994	0.751	58	3.73	1.52	54	4.85	1.97
2001	70	0.938	0.804	63	3.97	1.57	55	4.65	1.71
2002	70	1.020	1.124	63	4.15	1.65	56	4.84	1.85
1995--2002	521	0.871	0.825	439	3.81	1.69	377	4.63	2.00

[a] SPREAD is the difference between the bond yield to maturity and the yield of a corresponding currency Treasury security calculated by substituting the value for the life of the bond into the cubic equation that describes the benchmark yield curve of corresponding sovereign.

[b] SP-M-FI is calculated as the mean of long term issuer ratings assigned by Moody's, Standard and Poor's and Fitch-IBCA, converted to cardinal values as shown in Appendix 2a. A higher credit quality corresponds to a lower cardinal number.

[c] MBFS-FII is the mean of financial strength ratings assigned by Moody's/Fitch-IBCA, cardinalized as shown in Appendix 2b.

Table 2
Sample Descriptive Statistics -- Distribution by Country[a]

Country	No. of banks	SPREAD (%)		Ratings		AISD	Total assets	ROAA	Leverage	Net loans	LLR	Bad loans
		Mean	Std. dev.	SP-M-FI	MBFS-FII	(m. US$)	(bn. US$)	(%)		(%)	(%)	(%)
Austria	4	0.59	0.34	3.96	6.35	56.77	57.99	0.33	26.30	56.11	4.29	3.74
Belgium	2	0.67	0.34	4.09	4.25	64.78	229.00	0.55	26.88	40.64	1.88	2.83
Denmark	1	0.24	0.11	NA	NA	1,408.69	5.75	0.16	18.30	33.26	1.29	1.54
France	13	0.75	0.48	4.61	5.53	403.40	191.00	0.56	25.91	50.04	4.31	6.12
Germany	11	0.59	0.47	2.71	5.26	213.54	260.00	0.21	35.58	49.67	2.37	2.79
Ireland	1	0.99	0.31	4.58	4.00	158.38	56.36	1.25	16.22	66.99	1.07	1.73
Italy	5	1.76	2.01	5.79	6.77	224.26	99.51	0.44	17.81	59.06	3.76	8.21
Luxembourg	3	0.87	0.60	3.67	3.30	29.16	31.18	0.62	29.25	17.55	NA	NA
Netherlands	7	0.49	0.27	2.78	3.26	239.48	222.00	0.64	20.38	62.31	1.26	1.63
Norway	1	1.75	1.07	6.00	NA	106.44	36.06	0.91	15.75	71.06	2.47	1.62
Spain	4	1.68	1.03	4.53	4.18	200.00	213.00	0.76	15.91	48.78	3.00	2.78
Sweden	2	2.09	1.53	5.03	5.22	150.00	101.00	0.63	24.27	56.99	1.04	2.32
Switzerland	6	0.70	0.44	2.87	2.81	224.14	211.00	0.42	19.10	55.43	3.95	4.47
UK	10	1.00	0.46	3.41	3.29	330.56	188.00	0.81	21.08	65.19	1.27	2.21
Total	70	0.87	0.82	3.81	4.63	260.17	179.00	0.53	24.35	53.58	2.90	3.99

[a] SPREAD is the difference between the bond yield to maturity and the yield of a corresponding currency Treasury security obtained by substituting the bank debt maturity in the cubic equation that describes the benchmark yield curve of corresponding sovereign. *SP-M-FI* is the mean of traditional credit ratings (Standard and Poor's, Moody's and Fitch-IBCA) cardinalized as shown in Appendix 2a. *MBFS-FII* is the mean of financial strength (Moody's) and individual (Fitch-IBCA) bank specific ratings (cardinalized values). *AISD* is the US dollar-equivalent amount outstanding. *ROAA* is the ratio of annual net income to the average of the preceding and current year-end total assets. *Leverage* is the ratio of total (book) liabilities to the book value of equity. *Net loans* -- the ratio of net loans to total assets. *LLR* is the reserve for loan losses expressed as percentage of total loans. *Bad loans* -- the ratio of total problem loans to total (net) loans. *NA* = data non available

Table 3
SPREAD -- Distribution by Rating Classes[a]

	N	Mean	Std. dev.	Minimum	Maximum	Quartiles		
						Lower	Median	Upper
Panel A: Traditional ratings (S&P, Moody's, and Fitch-IBCA)								
AAA/Aaa	51	0.34	0.28	–0.34	1.46	0.23	0.30	0.45
AA/Aa	251	0.84	0.57	–0.06	4.94	0.47	0.72	1.10
A	112	1.22	1.31	–0.88	7.78	0.46	0.90	1.27
BBB/Baa	3	1.26	0.53	0.66	1.68	0.66	1.43	1.68
NR	104	0.83	0.68	–1.01	3.20	0.39	0.59	1.14
Total	521	0.87	0.82	–1.01	7.78	0.40	0.68	1.10
Panel B: Financial strength ratings (Moody's and Fitch-IBCA)								
A	43	0.50	0.41	–0.34	1.73	0.23	0.48	0.71
B	212	0.92	0.70	–0.06	5.12	0.48	0.77	1.13
C	87	1.09	1.39	–0.33	7.78	0.39	0.56	1.16
D	20	0.82	0.47	–0.02	1.94	0.47	0.80	1.03
NR	159	0.79	0.62	–1.01	3.20	0.37	0.64	1.10
Total	521	0.87	0.82	–1.01	7.78	0.40	0.68	1.10

[a] SPREAD is the difference between the bond yield to maturity and the yield of a corresponding currency Treasury security obtained by substituting the value for the life of the bond into the cubic equation describing the benchmark yield curve of corresponding sovereign. The traditional ratings are represented by the mean of long term issuer ratings assigned by Moody's, Standard and Poor's, and Fitch-IBCA, cardinalized as shown in Appendix 2a. The financial strength ratings are represented by the mean of the bank specific ratings assigned by Moody's and Fitch-IBCA (cardinalized values). The AA class includes the AA+, AA, AA– sub-classes, etc. *NR* = no rating available

Table 4
Description of the Main Explanatory Variables

Variable	Definition	Expected sign
ROAA	Return on average assets, calculated by dividing the annual net income to the average of the preceding and current year-end total assets	+/–
Cooke	Total capital adequacy ratio calculated according to Basel I	–
Leverage	Financial leverage, calculated as the ratio of total (book) liabilities to the book value of equity	+
NetLoans	Ratio of net loans to total assets, a measure of the opaqueness of banking firm's assets	+
Liquidity	Liquidity ratio, indicating what percentage of customer and short term funds could be met if they are suddenly withdrawn	–
LLR	Ratio of loan loss reserves to total (gross) loans, indicating how much of the total credit portfolio has been provided for but not charged off	+/–
BadLoans	Ratio of total problem loans to total (net) loans, a proxy for the quality of the loan portfolio	+
OBSA	Ratio of total off-balance sheet activities to total assets	–
ROAA*Lev	Product of ROAA and Leverage	–
LLR*Lev	Product of LLR and Leverage	–
BadLoans*Lev	Product of BadLoans and Leverage	–
ln(AISD)	Log of the outstanding amount of the issue, expressed in thousand US$, a proxy for liquidity effects on spreads	–
Maturity	Remaining maturity, expressed in years	+
α_t, t={95,…,02}	"Year" dummies, quantifying the inter-temporal variations in bond market conditions. One of the eight dummies (α_{1995}) was eliminated to avoid collinearity in the data	+
Recession	Takes the value of 1 if the economy is in recession and 0 if it is in expansion. We used the OECD *Composite Leading Indicators* to identify the troughs and peaks of the business cycle in each European country	+
France, Germany, Sweden, Switzerland, UK	"Country" dummy variables, capturing both differences in macroeconomic conditions and differences in safety nets across countries	+/–
Subordinated	Takes the value of 1 if the (unsecured) debt has a subordinated status and 0 otherwise	+
Split	Dummy variable equal to 1 if the bank issuer received a rating from Moody's that is different from the rating it received from S&P. According to Morgan (2002), split ratings are a sign that the bank's financial condition is opaque to investors	+
Split*Recession	Product of Split and Recession, to investigate Santos's (2006) thesis that the impact of split ratings on credit spreads in recessions is different from the corresponding impact in expansions; we consider the use of split ratings both when the risk measure is average ratings and when accounting ratios are used as risk proxies	+
TBTF	Ratio of total assets of bank *i* at the end of the year *t* to the maximum total assets at the end of the same year; alternative measures of the TooBigToFail variable, also used by Sironi (2003), are discussed in §5.4	–
Support	"External support" dummy variable, taking the value of 1 if the issuer is either a public-sector bank or a bank that benefits from explicit/implicit governmental guarantees and 0 otherwise. The presence of explicit/implicit guarantees is confirmed by a Fitch–IBCA Support rating equal to 1	–

Table 5
OLS *Pooled* Regressions: Traditional Ratings, Financial Strength (Bank-Specific) Ratings, and Governmental Guaranties[a]

Independent	Traditional ratings			Financial strength ratings			
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	3.254***	3.554***	3.364***	4.053***	4.026***	4.434***	4.528***
	(3.102)	(3.376)	(3.255)	(3.838)	(3.817)	(3.982)	(4.345)
SP-M-FI	0.081***	0.064***	0.079***	–	–	–	–
	(3.967)	(3.354)	(3.860)				
MBFS-FII	–	–	–	0.060***	0.061***	0.047***	0.092***
				(3.292)	(3.357)	(2.809)	(4.161)
Split	–	0.204***	0.131	0.308***	0.141	0.262***	0.046
		(2.919)	(1.506)	(3.801)	(1.486)	(3.058)	(0.342)
Split*Recession	–	–	0.334**	–	0.352**	–	0.273*
			(2.204)		(2.130)		(1.797)
ln(AISD)	–0.265***	–0.297***	–0.274***	–0.337***	–0.336***	–0.354***	–0.388***
	(–3.241)	(–3.626)	(–3.399)	(–3.992)	(–3.986)	(–4.063)	(–4.557)
Maturity	0.019**	0.014*	0.022***	0.022***	0.024***	0.019**	0.024***
	(2.382)	(1.748)	(2.667)	(2.632)	(2.834)	(2.185)	(2.700)
Subordinated	0.001	0.100	–0.055	–0.076	–0.078	0.055	–0.126
	(0.016)	(1.113)	(–0.607)	(–0.725)	(–0.739)	(0.613)	(–1.176)
Germany	–0.047	0.082	–0.002	–0.078	–0.087	–0.119*	–0.217***
	(–0.693)	(1.219)	(–0.029)	(–1.061)	(–1.208)	(–1.640)	(–2.655)
UK	0.205*	0.340***	0.213*	0.373***	0.339**	0.208*	0.325**
	(1.746)	(2.870)	(1.749)	(2.769)	(2.472)	(1.703)	(2.305)
Switzerland	0.026	0.136	0.048	0.662***	0.569**	0.671***	0.487**
	(0.244)	(1.395)	(0.491)	(2.918)	(2.456)	(3.189)	(2.279)
France	–0.115	0.074	–0.159	–0.006	–0.007	0.047	–0.072
	(–0.951)	(0.653)	(–1.320)	(–0.048)	(–0.058)	(0.405)	(–0.527)
Sweden	1.001**	1.030**	0.926**	1.041**	1.020**	0.855*	0.986**
	(2.012)	(2.162)	(1.979)	(2.195)	(2.198)	(1.800)	(2.015)
TooBigToFail	–	–	–	–	–	–	0.484**
							(2.376)
Support	–	–	–	–	–	–0.213***	–0.144*
						(–3.185	(–1.841)
Fa	9.958***	13.372***	10.210***	10.010***	9.777***	10.182***	10.757***
N	417	417	417	362	362	362	362
Adjusted R2	0.256	0.349	0.285	0.298	0.304	0.326	0.363

[a] Dependent variable is SPREAD (%) calculated as difference between actual yields on the bank debt and the constructed yield on a corresponding treasury security with the same maturity. Explanatory variables are defined as follows: *SP-M-FI* -- the average traditional credit rating assigned by S&P, Moody's, and Fitch, converted to cardinal values; *MBFS-FII* -- the average financial strength rating (cardinalized values); *Split* -- dummy variable that takes the value of 1 if Moody's ≠ S&P; *Split*Recession* -- the product of *Split* and *Recession* (a dummy that equals 1 if the economy is in recession); *ln(AISD)* -- the log of the US dollar-equivalent amount of the issue (in thousand); *Maturity* -- the remaining maturity expressed in years; *Subordinated* equals 1 if the bond is subordinated; *Germany*, *UK*, *Switzerland*, *France*, *Sweden* -- country dummies equal to 1 if the issuing bank is headquartered in the corresponding country; *TooBigToFail* -- the ratio of total assets of bank *i* at the end of the year *t* to the maximum total assets at the end of the same year; *Support* equals 1 if the issuing bank is a "public-sector" one (i.e. either government-owned or having a Fitch-IBCA Support rating equal to 1). All regressions include year dummies (not reported). Equations are estimated by OLS (*pooled*). Estimated standard errors are computed using White's method. Heteroskedasticity-consistent *t*-statistics are reported in parentheses below each coefficient estimate. *F*a -- regression *F*-statistic (df = [Ncoeff–1], [Nobs–Ncoeff]).

***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 6

Within Regressions: Traditional Credit Ratings, Financial Strength Ratings, and Governmental Guaranties[a]

Independent	Traditional ratings			Financial strength ratings				
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SP-M-FI	0.190***	0.189***	0.192***	–	–	–	–	–
	(4.477)	(4.493)	(4.580)					
MBFS-FII	–	–	–	0.144***	0.144***	0.153***	0.127***	0.149***
				(5.849)	(6.011)	(6.128)	(5.023)	(5.626)
Split	–	0.155*	–0.018	0.046	–0.064	–0.068	0.005	–0.063
		(1.677)	(–0.174)	(0.592)	(–0.720)	(–0.776)	(0.048)	(–0.692)
Split*Recession	–	–	0.166*	–	0.228**	0.254**	0.211**	0.252**
			(1.823)		(2.173)	(2.408)	(2.059)	(2.368)
TooBigToFail	–	–	–	–	–	–1.001***	–	–0.951**
						(–2.651)		(–2.463)
Support	–	–	–	–	–	–	–0.370*	–0.125
							(–1.728)	(–0.645)
Fa	131.741***	116.587***	103.526***	105.852***	95.337***	86.542***	86.157***	78.460***
Fb	9.170***	8.096***	8.942***	8.817***	8.906***	8.594***	8.504***	8.015***
N	417	417	417	362	362	362	362	362
Adjusted R2	0.672	0.674	0.674	0.684	0.687	0.690	0.688	0.689

[a] Dependent variable is SPREAD calculated as difference (expressed in percentage) between actual yields on the bank debt and the constructed yield on a corresponding treasury security with the same maturity. Explanatory variables are defined as follows: *SP-M-FI* -- the average traditional credit rating assigned by S&P, Moody's, and Fitch, converted to cardinal values; *MBFS-FII* -- the average financial strength rating (cardinalized values); *Split* is a dummy variable that takes the value of 1 if Moody's ≠ S&P; *Split*Recession* -- the product of *Split* and *Recession* (a dummy that equals 1 if the economy is in recession); *αt* -- year dummies (not reported); *TooBigToFail* is the ratio of the issuing bank's total assets to the total assets of the largest bank in the sample in the year of the observation; *Support* equals 1 if the issuer is a "public" bank (i.e. either government-owned or having a Fitch-IBCA Support rating equal to 1). Equations are estimated by OLS with inclusion of fixed effects (unreported intercept terms). Estimated standard errors are computed using White's method. Heteroskedasticity-consistent *t*-statistics are reported in parentheses below each coefficient. *F*a -- regression *F*-statistic (df = [*N*coeff–1], [*N*obs–*N*coeff]); *F*b -- heterogeneity specification test: *pooled* model *vs*. *fixed effects* model (see e.g. Hsiao, 2003).

***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 7
OLS (*Pooled* & *Within*) Regressions: Accounting Variables[a]

Independent	OLS -- pooled				OLS -- fixed effects	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Constant	2.655***	3.125***	5.681***	6.172***	–	–
	(4.494)	(3.798)	(5.170)	(5.234)		
ln(AISD)	–0.191***	–0.231***	–0.435***	–0.443***	–	–
	(–3.687)	(–3.510)	(–5.725)	(–5.510)		
Maturity	0.022***	0.039***	0.003	0.030*	–	–
	(3.129)	(3.368)	(0.182)	(1.942)		
Subordinated	0.293***	0.182*	0.240**	0.527***	–	–
	(3.991)	(1.900)	(1.987)	(4.296)		
Split	0.157**	0.277***	0.263**	0.006	0.184*	–0.007
	(2.174)	(3.218)	(2.430)	(0.058)	(1.787)	(–0.079)
Leverage	0.004	–	–0.006	–	0.031*	–
	(0.833)		(–0.617)		(1.912)	
Cooke	–	–0.000	–	–0.050*	–	–0.002
		(–0.092)		(–1.885)		(–0.075)
ROAA	0.271	0.531**	0.328	0.307	0.827**	–0.117
	(1.479)	(2.403)	(1.321)	(1.044)	(2.114)	(–0.334)
ROAA*Lev	–0.015**	–0.024**	–0.011	–0.008	–0.027*	0.012
	(–1.966)	(–2.386)	(–0.966)	(–0.615)	(–1.759)	(0.878)
NetLoans	–0.002	–0.004	0.003	0.002	0.003	–0.008
	(–1.064)	(–1.476)	(0.582)	(0.312)	(0.480)	(–1.118)
Liquidity	–0.004**	0.001	0.007*	0.011**	–0.006	–0.013***
	(–2.178)	(0.233)	(1.799)	(2.365)	(–1.281)	(–2.606)
LLR	–	–	0.459***	0.403**	0.221	0.064
			(3.363)	(2.490)	(1.403)	(0.262)
LLR*Lev	–	–	–0.014***	–0.016***	–0.010*	–0.004
			(–2.886)	(–3.025)	(–1.868)	(–0.553)
BadLoans	–	–	–0.390***	–0.371***	–0.170	–0.227
			(–3.482)	(–3.273)	(–1.417)	(–1.380)
BadLoans*Lev	–	–	0.013***	0.013***	0.007*	0.011*
			(2.874)	(3.077)	(1.683)	(1.904)
OBSA	–	–	–0.000**	–0.000***	–	–
			(–2.473)	(–2.656)		
TooBigToFail	0.081	0.186	0.947**	0.374***	–0.769**	–1.365**
	(0.532)	(1.097)	(2.552)	(3.563)	(–2.252)	(–2.322)
Support	–0.102**	–0.177***	–0.271**	–0.316**	–0.618***	–0.372
	(–2.256)	(–2.683)	(–2.180)	(–2.129)	(–2.817)	(–1.499)
Fa	10.934***	7.435***	7.535***	6.874***	30.845***	32.293***
Fb	1.960*	2.264**	3.100***	2.778***	1.725	2.835***
Fc	–	–	4.689***	3.716***	1.139	4.350***
Fd	–	–	–	–	5.332***	6.883***
N	514	395	259	224	285	241
Adjusted R2	0.317	0.273	0.424	0.433	0.645	0.734

[a] Dependent variable is (end-of-January) SPREAD (%). *ln(AISD)* -- the log of the US dollar-equivalent amount of the issue (in thousand); *Maturity* -- the time to maturity (expressed in years); *Subordinated* equals 1 if the bond is subordinated; *Split* is a dummy variable that takes the value of 1 if Moody's ≠ S&P; *Leverage* -- the ratio of total (book) liabilities to the book value of equity; *Cooke* -- the total capital adequacy ratio under the Basle rules; *ROAA* -- the ratio of annual net income to the average of the preceding and current year-end total assets; *ROAA*Lev* -- the product of *ROAA* and *Leverage*; *NetLoans* -- the ratio of net loans to total assets; *Liquidity* -- a deposit run off ratio; *LLR* -- the reserve for losses expressed as percentage of total loans; *LLR*Lev* -- the product of *LLR* and *Leverage*; *BadLoans* -- the ratio of total problem loans to total (net) loans; *BadLoans*Lev* -- the product of *BadLoans* and *Leverage*; *OBSA* -- the ratio of total off-balance sheet activities to total assets; *TooBigToFail* is the ratio of the issuing bank's total assets to the total assets of the largest bank in the sample in the year of the observation; *Support* equals 1 if the issuer is a "public" bank (i.e. either government-owned or having a Fitch-IBCA Support rating equal to 1). All regressions include year dummies (not reported). Equations are estimated by OLS pooled and with inclusion of fixed effects (unreported intercept terms). Estimated standard errors are computed using White's method. Heteroskedasticity-consistent *t*-statistics are reported in parentheses below each coefficient estimate. *F*a -- regression *F*-statistic (df=[Ncoeff–1], [Nobs–Ncoeff]); *F*b -- *F*-statistic for the hypothesis that the *x* bank-specific variables' coefficients are jointly zero (df=*x*,[Nobs–Ncoeff]); *F*c -- *F*-statistic for the hypothesis that all *y* coefficients of the credit quality measures equal zero (df=y,[Nobs–Ncoeff]); *F*d -- specification test: *pooled* model *vs*. *fixed effects* model (see e.g. Hsiao, 2003).

***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 8
The Accounting Empirical Model: Correcting for the "Error in Variables" Problem[a]

Marginal contribution of each block of explanatory variables	Model 1		Model 2		Model 3	
	(A)	(B)	(A)	(B)	(A)	(B)
Control variables	15.528***	7.760***	10.311***	5.843***	3.831***	4.551***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Accounting variables	1.916*	2.117*	2.286**	1.925*	2.279**	2.698***
	(0.091)	(0.063)	(0.028)	(0.067)	(0.019)	(0.006)
N	436	320	318	229	226	182
Adjusted R2	0.216	0.198	0.288	0.203	0.254	0.303

[a] This table presents the partial *F* statistics and *p* values (in parentheses) for each block of explanatory variables (control variables and accounting variables, respectively). Dependent variable is (end-of-December) SPREAD (%). Model 1 includes the control variables (*viz. ln(AISD)*, *Maturity*, *Subordinated*, *Split*, *TooBigToFail*, *Support*, "country" dummies, and time fixed-effects), as well as the following accounting variables: *Leverage* (specification A) or *Cooke* (specification B), *ROAA*, *ROAA***Lev*, *NetLoans*, and *Liquidity*. Model 2 includes the credit-quality measures *LLR*, *LLR***Lev* in addition to all the explanatory variables included in Model 1. Finally, Model 3 (the "full" model) includes two other credit-quality measures, *BadLoans*, *BadLoans***Lev*, in addition to all the explanatory variables included in Model 2. Estimations are performed by using the standard two-stage least squares (TSLS) procedures on the pooled sample of banks. The bank-specific (accounting) variables are instrumented by the control variables, lagged accounting variables, and $SPREAD_{t-1}$.

***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.